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Modeling temporal variability of soil CO_2 emissions from an apple orchard in the Harran Plain of southeastern Turkey

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Abstract: Broad interest in reducing greenhouse gas emissions requires a better understanding of controls on carbon dioxide (CO_2) release under different agricultural management practices. The objective of this study was to investigate and model seasonal variation of soil CO_2 emissions from an apple orchard field (*Malus domestica* L. 'Starkrimson'). Soil CO_2 emissions from an apple orchard managed with common practices were measured weekly over a 3-year period (May 2008 to May 2011) from both under the crowns of trees (CO_2-UC) and between rows (CO_2-BR) using a soda lime technique and were modeled using available environmental data. The study area is located in the Harran Plain of southeastern Turkey and has a semiarid climate. The weekly soil CO_2 emissions ranged from 87.8 to 1428 kg week^{-1} ha^{-1}, from 74.6 to 835 kg week^{-1} ha^{-1}, and from 88.6 to 1087 kg week^{-1} ha^{-1} for CO_2-UC, CO_2-BR, and the average of both (CO_2-AVG), respectively, and showed a pronounced seasonal pattern with the lowest emissions in winter (January and February) and the highest emissions during the growing season (April to December). Relative to 2008 emissions, 2009 CO_2 emissions increased by approximately 75%, and 2010 emissions increased by approximately 88%. Comparison of 3 models (multiple linear regression, principal component regression, and multivariate adaptive regression splines) showed that multivariate adaptive regression splines provided the best performance in modeling soil CO_2 emissions, explaining overall variation of 64%, 56%, 76%, and 53% in CO_2-AVG for the first, second, third, and all three 3 periods, respectively. In conclusion, overall findings showed that soil CO_2 emissions could be modeled by available environmental data such as air and soil temperature.

Key words: Soil CO_2 emission, multivariate statistical analysis, principal component analysis, principal component regression, multivariate adaptive regression splines

1. Introduction

Increased emission of greenhouse gases such as CO_2, methane (CH_4), and nitrous oxide (N_2O) to the atmosphere is closely associated with land use change, the use of fossil fuels, forest fires, emissions from automobiles, agricultural production, and other anthropogenic activities (Sauerbeck, 2001). The CO_2 concentration of the atmosphere has changed significantly since the Industrial Revolution, increasing from 280 ppm to 390 ppm (August 2011 Mauna Loa Station, NOAA; http://co2now.org/Current-CO2/CO2-Now/noaa-mauna-loa-co2-data.html), and it may double by the end of the 21st century if greenhouse gases continue being emitted (Lal, 2003). Soils contribute about 20% of the total CO_2 released to the atmosphere (Sauerbeck, 2001). Better management of soil organic carbon can reduce greenhouse gas emissions and increase soil fertility (Sauerbeck, 2001).

Monitoring CO_2 fluxes from soils can reveal important information about microbial activity, plant root respiration, soil–atmosphere interactions, soil energy and carbon budgets, and plant production, allowing us to better understand trends and find ways to mitigate emissions (Lal, 2003). The amounts of CO_2 released from the soil to the atmosphere varies greatly based on different land use types, agricultural activities, soil characteristics, and climate (Smith et al., 2000), and it generally ranges from 0.1 to 6 g CO_2 m^{-2} h^{-1} for agricultural soils (Sauerbeck 2001). Extensive research documents how temporal and spatial variations in CO_2 emissions are controlled by soil temperature (Almaraz et al., 2009), soil water content (La Scala et al., 2006), soil organic matter content and substrate quality (Frank et al., 2006), and interaction between significant properties (Pangle and Seiler, 2002). These variables impact the activity of roots and

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organisms as well as change the amount of CO_2 released from soils. Environmental variables have been related to soil CO_2 emissions using multiple linear regressions and exponential and polynomial regressions (Almaraz et al., 2009; Mapanda et al., 2010).

Researchers reported that soil CO_2 released varied greatly under different vegetation types and land uses (Iqbal et al., 2009). In particular, cropped soils can release 2-fold to 3-fold higher CO_2 emissions relative to bare soils (Rastogi et al., 2002). Soil CO_2 emissions from annual crops or forests are well documented (Almaraz et al., 2009). However, there are few results reported on CO_2 emissions from soils under orchard crops like apple, which covers large areas in Turkey (Tufekcioglu et al., 2009). Compared to cultivated crops, orchard crops have deeper roots, require less plowing, and have less residue removal, all of which contributes to root and microbial activity. Despite abundant studies of CO_2 emissions from soils, there is little or no work with high-frequency sampling in orchard systems.

The objectives of the current study were to quantify seasonal variation of soil CO_2 emissions from apple orchard soils at a weekly time scale and to model seasonal variations of soil CO_2 emissions using multiple linear regression (MLR), principal component regression (PCR), and multivariate adaptive regression splines (MARS) using available environmental variables.

2. Materials and methods

2.1. Study site

CO_2 emissions data were collected from an apple orchard located in the experimental farm of Harran University, Şanlıurfa, southeastern Turkey (37°10′N, 38°59′E). The study area has a semiarid climate with a mean annual temperature, precipitation, and evaporation rate of 17.2 °C, 365.2 mm, and 1848 mm, respectively. The area receives most of its precipitation from November to April. Temperatures can rise up to 45 °C during summer. Climatic data including weekly average air temperature, soil temperature at different depths (5, 10, 20, 50 and 100 cm; ST5, ST10, ST20, ST50, and ST100, respectively), precipitation (mm), and relative humidity (%) were obtained from a weather station located near the study site.

The experimental farm is approximately 520 m above sea level. The soils within the study area are silty loam and clay formed on calcareous parent material. Soils were classified as clay loam and as Vertisol according to soil taxonomy (Soil Survey Staff, 2006). In general, the soils are characterized with low amounts of organic matter and high amounts of $CaCO_3$ and clay contents.

The apple trees, *Malus domestica* L. 'Starkrimson', were planted in 1999. The rows between the trees are of about 5 m. During the growing season, the apple trees receive N, P, and K fertilizer in June and August (a total of 25 kg day^{-1}, 18–18–18 composite), sufficient water is applied by drip irrigation, and trees receive other regular growth care such as plowing of the top 10–15 cm of surface layer between the rows, hoeing for weed reduction 3 to 4 times a year, pruning, and pest control. Description and timing of all the management and regular care practices applied are listed in Table 1.

2.2. Soil analyses

A composite soil sample was taken at the surface (0–30 cm) and at 2 subsurface depths (30–60 and 60–90 cm). Soils were air-dried and sieved to 2 mm. We quantified particle size distributions using the hydrometer method (Bouyoucos, 1926), organic matter content by the Walkley–Black method (Nelson and Sommers, 1982), carbonates using a calcimeter (Kacar, 1994), soil pH using a 1:2.5 soil/water suspension (McLean, 1982), and electrical conductivity (EC) in soil extracts using a conductivity meter (Janzen, 1993). Soil-available P and K levels were determined using an ICP-AEAS (Varian-Vista, Palo Alto, CA, USA) after $NaHCO_3$ extraction (pH 8.5) (Olsen and Sommers, 1982) and NH_4OAc extraction (Knudesen et al., 1982), respectively. Soil micronutrients were determined after DTPA extraction (Lindsay and Norvell, 1978). All analyses were performed using 3 replicates, with averages reported in the results. Soil water contents (SWCs) at both underneath the crown of the trees (CO_2-UC) and between rows (CO_2-BR) were measured after soils were dried at 105 °C; these soil samples were extracted concurrently with the measurement of soil CO_2 emissions.

2.3. Soil CO_2 emissions

Over a 3-year period from May 2008 to May 2011, we used the soda lime method (Edwards, 1982) to conduct weekly measurements of CO_2 emissions from both underneath the crown of the trees (CO_2-UC) and between rows (CO_2-BR). Procedures of the soda lime technique used in the present study and calculations of amount of emitted CO_2 were performed according to earlier studies that successfully applied the methodology (Janssens and Ceulemans, 1998; Grogan, 1998; Keith and Wong, 2006). The soda lime technique is advantageous as a long-term monitoring tool due to its ease and the inexpensive nature of its implementation (Janssens and Ceulemans, 1998; Keith and Wong, 2006). Emissions were quantified as the average of 5 replicates (sampling points) from each site (underneath the crown of trees and between rows). Our CO_2 emission measurements were conducted using 40 g soda lime ($Ca(OH)_2 + H_2O$) with particle size of 3–5 mm. The lime was dried at 105 °C for 24 h, and then it was taken into a desiccator for cooling. After cooling, it was weighed using a scale with 0.0001 sensitivity and added to numbered plastic PVC containers (3 cm tall and 100 cm^2 in surface area), and then covered with a tight lid to keep

Table 1. Regular agricultural activities performed during the study period.

		Agricultural practices					
Years	Months†	Plowing	Irrigation	Pesticide app.	Hoeing$^{\beta}$	Fertilization	Pruning
2008	May	X	X	X			
	Jun	X	X	X		X	
	Jul		X		X		
	Aug	X	X	X		X	
	Sep		X				
	Oct	X	X	X			
	Nov						
	Dec						
2009	Jan			X			
	Feb						X
	Mar	X		X	X		
	Apr		X	X			
	May	X	X	X			
	Jun	X	X	X		X	
	Jul		X		X		
	Aug	X	X	X		X	
	Sep		X				
	Oct	X		X			
	Nov						
	Dec						
2010	Jan			X			
	Feb						X
	Mar	X		X	X		
	Apr		X	X			
	May	X	X	X			
	Jun	X	X	X		X	
	Jul		X		X		
	Aug	X	X	X		X	
	Sep		X				
	Oct	X		X			
	Nov						
	Dec						
2011	Jan			X			
	Feb						X
	Mar	X		X	X		
	Apr		X	X			

†: Months from May 2008 to end of May 2011; $^{\beta}$: performed for weeding.

the moisture in the container. At each sampling location, 1 PVC container with known mass of soda lime was quickly opened and placed inside a chamber with dimensions of 23 cm in width by 33 cm in height. The chamber was inserted 2 cm under the soil surface in order to prevent any interaction of soda lime with climate and to minimize gas leakage underneath the chamber as much as possible. A thick PVC lid (50 × 50 cm) was immediately placed on the chamber to seal it in order to make a shadow effect and minimize the temperature change within the chamber. A heavy stone was placed on each lid to protect the lid from wind or any other foreign objects. The starting time was recorded and the chambers were left for 1 week of incubation. After 1 week, PVC containers with soda lime were removed from chambers and quickly sealed with a tight lid, transported back to the nearby laboratory, dried for 24 h, and reweighed. Each week, the measurement point was changed and the chamber was placed on an adjacent spot in order to avoid any bias. In measurements, no additional water was used to moisturize the soda lime since it was thought that the moisture in the soil was enough to initiate the chemical reaction.

Cumulative monthly and yearly values were calculated by summing the weekly CO_2 emission values (Peng et al., 2001; Wilson and Al-Kaisi, 2008).

CO_2 emissions were calculated using the equation below (Keith and Wong, 2006):

$$F_{CO_2} = \frac{(C_{adsorbed} - C_{initial}) \times W}{t_{incubation} \times A} \quad , \tag{1}$$

where F_{CO_2} is emitted CO_2 g cm^{-2} day^{-1}, $C_{adsorbed}$ is the weight of soda lime after incubation (g), $C_{initial}$ is the weight of soda lime before incubation (g), $t_{incubation}$ is the incubation period (weeks), A is area of the chamber (cm^2), and W is the coefficient used to correct for the loss of water occurring during the reaction, taken as 1.69 (Grogan, 1998; Keith and Wong, 2006).

The amount of CO_2 emissions as calculated as g cm^{-2} day^{-1} was later converted into weekly and monthly values.

2.4. Data analysis

Statistical differences in soil CO_2 emissions between the 2 locations, (i.e. underneath tree crowns and between tree rows) were assessed using a 2-tailed t-test ($P < 0.01$ significance level) where weeks were used as replicates and locations as treatment.

One-way ANOVA with the least significant difference test was used at the $P < 0.05$ significance level in order to assess the significance of differences in mean annual soil CO_2 emissions, where months within each year were used as replicates and years as treatment. Statistical data analyses were performed using SPSS (SPSS Inc., Chicago, IL, USA).

2.5. Modeling of soil CO_2 emission

The relationship between environmental variables and soil CO_2 emissions were modeled using 3 methods; MLR, PCR, and MARS. Three different models were constructed for under canopy (CO_2-UC), between row (CO_2-BR), and orchard average (CO_2-AVG) locations for individual years as well as for the entire sampling period. We applied 2 approaches to MLR model development. In model 1 (MLR1), only individual effects of environmental variables were used; in model 2 (MLR2), interaction effects between soil and air temperature and variables such as relative humidity (RH), rainfall, and SWC (SWC underneath crown [SWC-UC] and SWC between rows [SWC-BR]) were included into the models. For PCR model development, the principal components (PCs) extracted were used as predictors. For MARS model development, we included both main effects and also interactions of all available environmental variables.

2.5.1. Multiple linear regression model

MLR models the relationship between more than one explanatory variable and a response variable by fitting a linear function to observed data. It is formulized as:

$$Y = \beta_O + \beta_1 x_1 + \beta_2 x_2 + ...\beta_n x_n \ , \tag{2}$$

where *Xs* are predictors that are environmental variables including SWCs and available meteorological parameters; *Y* is the estimate of variable of interest, which is soil CO_2 emission; and β_i represents linear coefficients. Statistical significance of parameters included in the MLR models was tested at $P < 0.05$ and $P < 0.01$. MLR modeling was performed in JMP® 7.0 software (SAS Institute Inc., Cary, NC, USA).

2.5.2. Principal component regression

PCR was performed after principal component analysis (PCA) was applied on the data set (environmental variables). The goal of PCA is to reduce the dimensionality of the data while retaining the variation present in the original data set. As a variable reduction and pattern recognition technique, the PCA method decomposes (transforms) the autocorrelated independent variables and finds new uncorrelated variables, called PCs, which are both orthogonal and weighted linear combinations of the original X variables. Extracted PCs were subsequently used to develop a regression model using PCR analysis. PCA and PCR were performed using JMP® 7.0 software (SAS Institute Inc.).

2.5.3. Multivariate adaptive regression splines

MARS is an explanatory data analysis (data mining) technique developed by Friedman (1991). The MARS technique uses basis functions to model predictor and response variables. For constructing the basis functions, MARS splits the data into subregions (splines) with different interval ending knots, which are the points in the slope where the regression coefficients change, and fits the data in each subregion using adaptive piecewise linear regression. These basis functions are then used as new predictor variables for modeling purposes. Each basis function may contain nonlinear and interaction factors (second and third order) among variables, as well as linear combinations. The final MARS model representing the relationship between the response variable (Y) and target variable (X) is the weighed sum of other basis functions:

$$Y = \beta_O + \Sigma\beta_i \times fi(X)\,, \tag{3}$$

where β_0 is a constant (intercept), β_i is a constant of fit, and Y is the final output.

The number of basis functions is determined using a forward stepwise procedure, where first a deliberately overfitted model is constructed. In order to measure lack of fit and avoid overfitting the data, MARS uses a modified form of the generalized cross-validation (GCV) criterion, which can be calculated as follows:

$$GCV = \frac{\frac{1}{n}\sum_{i=1}^{n}\left[y_i - f(x_i)\right]^2}{\left[1 - \frac{C(m)}{n}\right]^2}\,, \tag{4}$$

where n is the number of observations. The numerator, or the sum of squared errors, measures the lack of fit on the m basis function models. f(xi) is the function of the MARS prediction model and y is the dependent variable, in this case soil CO_2 emissions. The denominator represents the penalty to account for the increased variance associated with higher model complexity and a larger number of basis functions in the model. C(m) is the cost-complexity measure of a model containing m basis functions, used to penalize the model complexity in order to avoid overfitting by introducing a cost for each basis function added into the model. In other words, more basis functions in the model provide both greater flexibility and more complexity. MARS attempts to keep the model as least complex as possible, and the optimum model has the lowest GCV value. MARS was performed with MARS™ software for Windows (v. 2; Salford Systems, San Diego, CA, USA).

3. Results

Soil properties at all the explored depths are shown in Table 2. Most soil characteristics were similar at surface and subsurface depths. Soils are of clay texture at all depths. The soils were alkaline (pH > 7) with lime content (>19%). The soils had low levels of salinity (EC < 4 dS m^{-1}). Soils had low soil organic matter content ranging from 0.48% to 1.16%. Both surface and subsurface soils were high in K, which ranged from 91 to 165 kg da^{-1}, but moderate to low in P, ranging from 0.9 to 6.3 kg da^{-1} due to the high lime content.

Figure 1 presents the weekly fluctuation of soil CO_2 emissions (kg ha^{-1} $week^{-1}$) from both under tree crowns (CO_2-UC) and between rows (CO_2-BR). Under canopy emissions were always higher than between row emissions (Figure 1). A t-test demonstrated a significant difference ($P < 0.01$) for each year analyzed separately as well as across the entire 3-year data set. As expected, there was pronounced seasonality in weekly soil CO_2 emissions, with higher emissions in the growing season (June to September) and lower emissions during the winter dormancy period (December to February).

Annual average air temperature was 18.7, 19.5, and 20.1 °C in the first (2008–2009), second (2009–2010), and third (2010–2011) year, respectively. Total annual precipitation rates were 405, 427, and 348 mm, respectively. The most precipitation was received during the fall and winter. Precipitation had the highest coefficient of variation (CV)

Table 2. Some selected soil chemical and physical properties at different depths.

					Plant available nutrients		DTPA-extractable micronutrients				Soil particle size			
	$CaCO_3$	SOM*	pH	EC	P	K	Fe	Cu	Zn	Mn	Sand	Clay	Silt	Texture
Depth (cm)	%			(dS m^{-1})	(kg da^{-1})		(ppm)					(%)		
0–30	19.3	0.61	7.83	0.96	6.34	164.1	5.1	2.1	0.3	14.0	21	56	23	Clay
30–60	20.5	1.16	7.76	1.14	1.31	105.8	6.4	1.7	0.3	13.4	21	58	21	Clay
60–90	22.8	0.48	7.79	1.16	0.98	90.7	6.5	1.5	0.3	9.7	23	58	19	Clay

*: Soil organic matter.

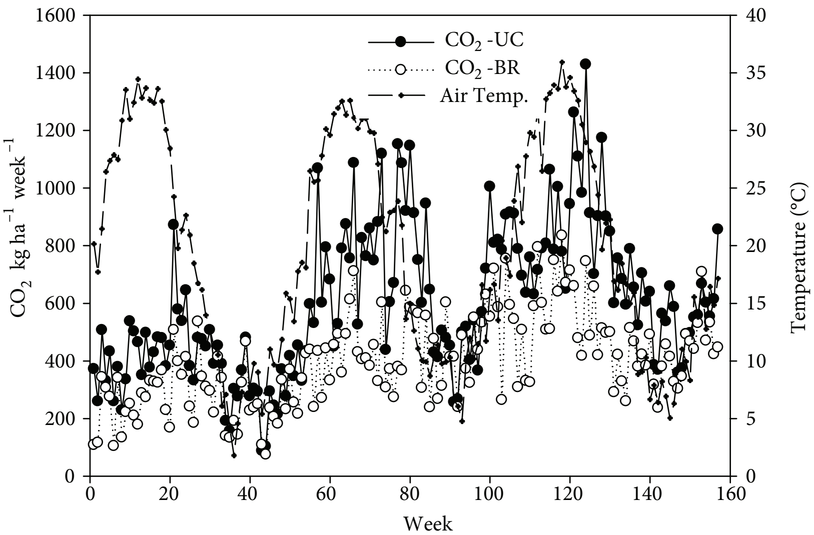

Figure 1. Weekly variations of soil CO_2 emissions from underneath the crown (CO_2-UC) and between rows (CO_2-BR), along with weekly air temperature during the course of the study period.

among all parameters; soil CO_2 emissions had a moderate CV and low skewness. At our site, the third year was the warmest and driest year. The average air temperature gradually increased between 2008 and 2011. Weekly measurements of soil CO_2 emissions had a very broad range of 88.6 to 1087 kg ha^{-1} week^{-1}, with the highest rates in the third year ranging between 359 and 1428 kg ha^{-1} week^{-1} under the canopy and from 237 to 835 kg ha^{-1} week^{-1} between rows (Table 3).

Cumulative monthly emissions are shown in Figure 2. Under canopy and between row emissions generally followed a similar pattern, increasing in the spring through the summer and peaking in the early fall. There were some months, however, where the highest cumulative flux was observed under the canopy, but this was not concurrent with the highest between row cumulative emissions.

Annual cumulative soil CO_2 emissions increased during the observation period totaling 20,013, 35,869, and 38,014 kg ha^{-1} year^{-1} under the canopy and 13,797, 23,182, and 25,416 kg ha^{-1} year^{-1} between rows. Statistical comparisons of mean annual soil CO_2 emissions showed that emissions in the first year were statistically different than those of the other 2 years, while the difference between the second and third year was not statistically different ($P < 0.05$) (Table 4).

The relationships between soil CO_2 emissions and environmental variables were assessed using pairwise correlation (Table 5) and PCA (Table 6). Pairwise correlation results show CO_2-UC had a statistically significant positive correlation with air and soil temperature and had a negative correlation with RH. For soil temperature, the highest correlation coefficient was obtained between soil temperature at 100-cm depth (ST100) and soil CO_2 emissions. Between row emissions were similarly positively correlated with temperature values and negatively correlated with RH. The relationship between precipitation and soil CO_2 emission was negative but not significant. Data analysis using PCA showed that emissions were negatively correlated with PC1 and positively correlated with PC6, with these 2 PCs explaining most of the relationships among environmental parameters (Table 6).

Model success varied among years as well as across applications for under canopy versus between row data. The weakest results were obtained in the models constructed for CO_2-BR in the second year, while the best were for CO_2-UC using all methods in the third year.

The success of model performance followed the order of MARS > PCR > MLR2 > MLR1. The MARS method outperformed all other methods, providing higher R^2 and lower root mean square error of prediction (RMSEP) values, except for in a few cases.

Most MLR models were statistically significant ($P \leq 0.01$, Table 7). In Model 1, where only individual effects were modeled, R^2 values ranged from 0.31 to 0.60 ($P \leq 0.01$ for the first, second, third, and all 3 years [2008–2011]) for CO_2-UC, from 0.11 to 0.39 ($P \leq 0.01$ for the second year and all years) for CO_2-BR, and from 0.23 to 0.61 ($P \leq 0.01$ for the third year and all years) for CO_2-AVG. In Model 2, which included interaction effects, R^2 values ranged from 0.41 to 0.68 ($P \leq 0.01$ for the first year, second year, third year, and all years) for CO_2-UC, from 0.19 to 0.44 ($P \leq 0.01$ for all years) for CO_2-BR, and from 0.34 to 0.68 ($P \leq 0.01$ for the first year, third year, and all years) for CO_2-AVG.

Table 3. Descriptive statistics of weekly soil CO_2 emissions and meteorological variables.

Variables	uom†	Mean	Max.¶	Min.±	SDβ	CVα	Kurtosis	Skewness
First year (2008–2009)								
CO_2-UC	(kg ha^{-1} $week^{-1}$)	384	871	87.8	137	0.36	2.2	0.55
CO_2-BR	(kg ha^{-1} $week^{-1}$)	265	536	74.6	105	0.40	−0.1	0.4
CO_2-AVG	(kg ha^{-1} $week^{-1}$)	325	689	88.6	113	0.35	1.1	0.39
Air temperature	(°C)	18.7	34.4	1.8	10	0.53	−1.3	0.13
Relative humidity	(%)	53	80.2	17.1	14.5	0.27	−0.06	−0.41
Soil temperature	(°C)	20.3	32.9	8.18	11.8	0.58	−1.4	0.11
Precipitation	(mm)	7.78	80.2	0	11.2	1.44	15.6	3.4
Soil water content	(%)	22.6	34.9	7.77	6.67	0.30	−0.91	−0.06
Second year (2009-2010)								
CO_2-UC	(kg ha^{-1} $week^{-1}$)	689	1151	256	240	0.35	−0.8	0.3
CO_2-BR	(kg ha^{-1} $week^{-1}$)	445	754	238	133	0.30	−0.6	0.4
CO_2-AVG	(kg ha^{-1} $week^{-1}$)	567	898	253	160	0.28	−0.8	0.3
Air temperature	(°C)	19.5	32.6	4.77	8.8	0.45	−1.5	0.07
Relative humidity	(%)	48.1	85.3	20.9	18.7	0.39	−1.2	0.4
Soil temperature	(°C)	20.7	31.5	9.8	7.6	0.37	−1.5	0.09
Precipitation	(mm)	8.22	89.4	0	17.9	2.18	8.9	2.9
Soil water content	(%)	24.4	41.8	9.27	8.07	0.33	−1.04	0.12
Third year (2010–2011)								
CO_2-UC	(kg ha^{-1} $week^{-1}$)	731	1428	359	224	0.31	0.99	0.85
CO_2-BR	(kg ha^{-1} $week^{-1}$)	488	835	237	143	0.29	−0.27	0.49
CO_2-AVG	(kg ha^{-1} $week^{-1}$)	609	1087	302	160	0.26	0.45	0.51
Air temperature	(°C)	20.1	35.9	5.1	9.7	0.48	−1.4	0.08
Relative humidity	(%)	43.6	79.4	1.56	16.7	0.38	−0.65	0.49
Soil temperature	(°C)	21.4	33.6	8.6	8.8	0.41	−1.5	−0.04
Precipitation	(mm)	6.3	57.2	0	11.9	1.89	5.9	2.3
Soil water content	(%)	20.5	34.9	3.88	8.32	0.41	−1.02	0.13

†: Units of measurements; ¶: maximum values; ±: minimum values; β: standard deviation ; α: coefficient of variation; CO_2-UC: soil CO_2 emissions from crowns of trees; CO_2-BR: soil CO_2 emissions between rows; CO_2-AVG: average of CO_2-UC and CO_2-BR.

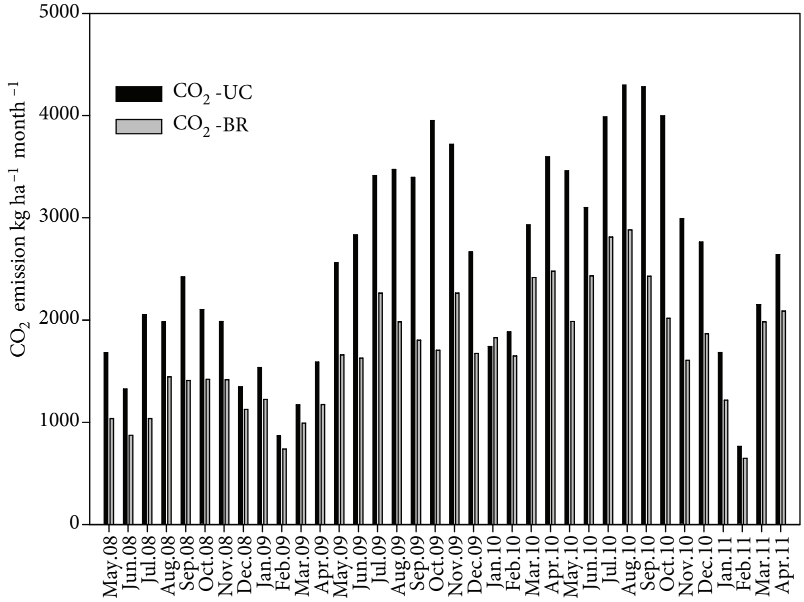

Figure 2. Cumulative monthly soil CO_2 emissions from underneath the crown (CO_2-UC) and between rows (CO_2-BR).

Table 4. Results of ANOVA analysis of mean annual soil CO_2 emissions.

	First year (2008–2009)	Second year (2009–2010)	Third year (2010–2011)
CO_2-UC	1671a	3013b	3010b
CO_2-BR	1156a	1944b	1996b
CO_2-AVG	1413a	2479b	2503b

Mean values followed by the same letter are not statistically significant at 0.05 level.
CO_2-UC: Soil CO_2 emissions from crowns of trees; CO_2-BR: soil CO_2 emissions between rows;
CO_2-AVG: average of CO_2-UC and CO_2-BR.

Air and soil temperature were significant in both Model 1 and 2 for the model covering all 3 years. Soil temperature was significant in almost all models except for the models constructed for CO_2-BR in the second and third years. Soil water content obtained between tree rows (SWC-BR) was significant in some cases, i.e. Model 1 constructed for CO_2-BR in the second year ($P \leq 0.05$) and Model 2 constructed for CO_2-BR ($P \leq 0.01$) and CO_2-AVG ($P \leq 0.05$) in the second year and in all 3 years. RH showed a significant effect only for the model constructed for all 3 years ($P \leq 0.01$). Precipitation was only statistically significant in Model 2 constructed for the second year ($P \leq 0.01$) and all years ($P \leq 0.05$). Air temperature and SWC-BR interactions and ST100 and SWC-BR interactions were significant ($P \leq 0.05$). Air temperature and RH in the model constructed for all 3 years as well as the interaction between ST100 and SWC-UC in 2010 were also significant ($P \leq 0.05$). Inclusion of interaction effects in MLR Model 2 improved overall R^2 values and reduced RMSEP, explaining higher variations in soil CO_2 emissions (Table 7).

Model R^2 values for PCR ranged from 0.14 to 0.69 (Table 8). PCR provided better results than the MLR 1 models but closer results to the MLR 2 models (Table 8). All models were statistically significant ($P < 0.05$), except those constructed for CO_2-BR and CO_2-AVG in the second year. In terms of significant PCs in the models, PC1, PC6, and PC7 were statistically significant for models in the first year. In the second year, PC10 instead of PC7 was significant, as well as PC1 and PC6. In the third year, principal components of PC1 and PC2 were highly significant, with rainfall highly weighted in PC2 (Table 9). Over the whole study period, the significance of PC9 and

Table 5. Correlation coefficients between weekly soil CO_2 emissions and environmental variables for all years' data (2008–2011).

	CO_2-UC	CO_2-BR	CO_2-AVG
CO_2-UC	1		
CO_2-BR	0.69**	1	
CO_2-AVG	0.95**	0.87**	1
SWC-UC	–0.11	–0.02	–0.08
SWC-BR	–0.44**	–0.15	–0.36**
Air temperature	0.41**	0.23**	0.37**
Relative humidity	–0.43**	–0.25**	–0.39**
Soil temperature at 5 cm	0.42**	0.24**	0.38**
Soil temperature at 10 cm	0.42**	0.23**	0.38**
Soil temperature at 20 cm	0.45**	0.24**	0.40**
Soil temperature at 50 cm	0.46**	0.24**	0.41**
Soil temperature at 100 cm	0.50**	0.25**	0.44**
Precipitation	–0.16*	–0.02	–0.12

*: Significant at 0.05 level; **: significant at 0.01 level; CO_2-UC: soil CO_2 emissions from crowns of trees; CO_2-BR: soil CO_2 emissions between rows; CO_2-AVG: average of CO_2-UC and CO_2-BR; SWC-UC: soil water content underneath of crown; SWC-BR: soil water content between rows.

PC10 varied. Highly weighted variables in these PCs were soil temperatures at various depths.

Model R^2 values of MARS ranged from 0.35 to 0.76. The values for GCV-R^2 ranged from 0.1 to 0.54, indicating low precision of model cross-validation (Table 10). The highest model significance was obtained for the last year as in the case of models constructed using MLR method: Model 1 and Model 2. The MARS modeling process orders model variables based on their significance. In most cases, soil temperature had the highest percent significance; exceptions were the second year and all 3 years, where RH in the MARS model constructed for CO_2-UC and air temperature for CO_2-AVG had the highest degrees of significance, respectively.

4. Discussion

Our weekly measurement of soil CO_2 emissions over a 3-year period provides a higher frequency and duration of emissions relative to available data (La Scala et al., 2006). In that work, La Scala et al. evaluated the soil CO_2 emissions in a short period of time; however, there are several studies with assessments over longer periods (Zhang et al., 2006; Mancinelli et al., 2010; Akburak and Makineci, 2013). Variation in the magnitude of emission peaks and troughs followed the air temperature pattern, with a few exceptions that can be attributed to management practices such as irrigation, fertilization, tillage and residue management, and crop rotation, which can affect the amount of CO_2 emissions by altering the physicochemical and biological properties of soils that control soil respiration (Baggs et al., 2006; La Scala et al., 2006).

Overall, emissions were higher than values reported for annual crops in earlier studies (Alvaro-Fountes et al., 2007; Schaufler, 2010). These rates were also higher than emissions from nearby wheat field (results not reported), which averaged weekly emissions of 224, 403, and 522 kg ha^{-1} $week^{-1}$ in the first, second, and third years as determined using the same methodology. In contrast, Iqbal et al. (2009) compared the soil CO_2 fluxes under different land covers (vegetables, forest, uplands, and orchard) and found that soils under forest and orchard management had lower CO_2 fluxes relative to other agricultural land uses. High soil CO_2 emissions in our study may be due to a couple of factors: high average temperatures, high soil $CaCO_3$, high oxidation rates, and high biomass content contributing to root respiration and ultimately fueling microbial growth through organic matter residue. Zhang et al. (2006) reported soil CO_2 emissions between 21,630 and 39,422 kg ha^{-1} $year^{-1}$ in subhumid forest ecosystems with over 1900 mm of annual precipitation. Their soil CO_2

Table 6. Explained variance by each principal component and correlations between principal components and environmental variables in the 3 years and all years combined.

	First year 2008–2009				Second year 2009–2010				Third year 2010–2011				All years 2008–2011			
	EV[†]	CO_2-UC	CO_2-BR	CO_2-AVG	EV	CO_2-UC	CO_2-BR	CO_2-AVG	EV	CO_2-UC	CO_2-BR	CO_2-AVG	EV	CO_2-UC	CO_2-BR	CO_2-AVG
PC1	73.47	–0.43**	–0.1	–0.31*	76.25	–0.4**	0.04	–0.28*	76.47	0.68**	–0.52**	–0.71**	74.77	–0.45**	–0.23**	–0.4**
PC2	10.83	0.13	0.07	0.11	11.4	0.13	0.04	0.12	10.75	0.22	0.28*	0.28*	9.87	0.09	0.09	0.1
PC3	9.61	0.12	0.06	0.1	8.24	–0.02	0.03	–0.006	8.24	–0.07	0.16	0.02	9.71	0.05	0.16	0.1
PC4	3.55	–0.1	–0.05	–0.09	1.86	–0.12	–0.12	–0.14	2.52	0.19	–0.02	0.12	2.42	–0.11	–0.08	–0.11
PC5	1.57	–0.07	–0.01	–0.05	1.5	–0.18	0.16	–0.07	1.23	–0.1	0.11	–0.02	2.17	–0.16	0.04	–0.09
PC6	0.86	0.43**	0.41**	0.45**	0.59	0.28*	0.26	0.32*	0.67	0.21	–0.04	0.13	0.88	0.25**	0.14	0.23**
PC7	0.09	0.11	0.33*	0.22	0.13	0.05	–0.08	0	0.09	–0.01	0.01	0	0.12	–0.11	–0.07	–0.1
PC8	0.01	0.15	0.23	0.2	0.01	–0.08	0.09	–0.02	0.03	0.07	0.01	0.06	0.02	–0.11	–0.2*	–0.16*
PC9	0.00	0.09	0.17	0.13	0.008	0.19	0.14	0.2	0.006	0.27	0.02	0.2	0.01	0.25**	0.15	0.23**
PC10	0.00	–0.21	–0.1	–0.17	0.002	0.32*	0.05	0.26	0.003	0.15	0.33*	0.25	0.00	–0.2*	–0.15	–0.2*

[†]: Explained variance; *: significant at 0.05 level; **: significant at 0.01 level; CO_2-UC: soil CO_2 emissions from crowns of trees; CO_2-BR: soil CO_2 emissions between rows; CO_2-AVG: average of CO_2-UC and CO_2-BR.

Table 7. Results of modeling of soil CO_2 emissions using MLR method.

	First year 2008-2009						Second year 2009-2010					
	Model 1			Model 2			Model 1			Model 2		
	CO_2-UC	CO_2-BR	CO_2-AVG	CO_2-UC	CO_2-BR	CO_2-AVG	CO_2-UC	CO_2-BR	CO_2-AVG	CO_2-UC	CO_2-BR	CO_2-AVG
$R^{2\dagger}$	0.38	0.13	0.28	0.68	0.36	0.57	0.31	0.11	0.23	0.51	0.38	0.45
RMSEP‡	115	105	102	91	98	87	212	134	150	197	124	138
P^{β}	**§	ns	*	**	ns	**	**	ns	ns	**	ns	ns
SWC-UC	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns
SWC-BR	ns	ns	ns	ns	ns	ns	ns	*	ns	ns	**	*
AT	*	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns
RH	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns
ST100	**	*	**	**	*	**	*	ns	*	**	ns	**
PRECIPT	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	**	ns
AT × SWC-UC				ns	ns	ns				ns	ns	ns
AT × SWC-BR				**	ns	*				ns	ns	ns
AT × RH				ns	ns	ns				ns	ns	ns
AT × PRECIPT				ns	ns	ns				ns	ns	ns
ST100 × SWC-UC				ns	ns	ns				ns	ns	ns
ST100 × SWC-BR				**	ns	*				ns	ns	ns
ST100 × RH				ns	ns	ns				ns	ns	ns
ST100 × PRECIPT				ns	ns	ns				ns	ns	ns

†: Coefficient of determination; ‡: root mean square error of estimation; $^{\beta}$: significance level; §: variables in the model; *: significant at 0.05 level; **: significant at 0.01 level; ns: nonsignificant; CO_2-UC: soil CO_2 emissions from crowns of trees; CO_2-BR: soil CO_2 emissions between rows; CO_2-AVG: average of CO_2-UC and CO_2-BR; SWC-UC: soil water content underneath of crown; SWC-BR: soil water content between rows; AT: air temperature (°C); RH: relative humidity (%); ST100: soil temperature at 100 cm; PRECIPT: precipitation (mm).

Table 7 continued.

	Third year 2010-2011						All years 2008-2011					
	Model 1			Model 2			Model 1			Model 2		
	CO_2-UC	CO_2-BR	CO_2-AVG	CO_2-UC	CO_2-BR	CO_2-AVG	CO_2-UC	CO_2-BR	CO_2-AVG	CO_2-UC	CO_2-BR	CO_2-AVG
$R^{2\dagger}$	0.6	0.39	0.61	0.68	0.44	0.68	0.33	0.12	0.26	0.41	0.19	0.34
RMSEP‡	152	119	106	148	126	106	214	153	168	206	151	163
P^{β}	**	**	**	**	*	**	**	**	**	**	**	**
SWC-UC	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns
SWC-BR	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	**	*
AT	ns	*	ns	ns	ns	ns	**	ns	**	**	ns	*
RH	ns	ns	ns	ns	ns	ns	**	**	**	**	**	**
ST100	**	ns	*	**	ns	*	**	*	**	**	**	**
PRECIPT	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	*	ns
AT × SWC-UC				ns	ns	ns				ns	ns	ns
AT × SWC-BR				ns	ns	ns				**	*	**
AT × RH				ns	ns	ns				ns	*	*
AT × PRECIPT				ns	ns	ns				ns	ns	ns
ST100 × SWC-UC				*	ns	ns				ns	ns	ns
ST100 × SWC-BR				ns	ns	ns				**	**	**
ST100 × RH				ns	ns	ns				ns	ns	ns
ST100 × PRECIPT				ns	ns	ns				ns	ns	ns

†: Coefficient of determination; ‡: root mean square error of estimation; β: significance level; §: variables in the model; *: significant at 0.05 level; **: significant at 0.01 level; ns: nonsignificant; CO_2-UC: soil CO_2 emissions from crowns of trees; CO_2-BR: soil CO_2 emissions between rows; CO_2-AVG: average of CO_2-UC and CO_2-BR; SWC-UC: soil water content underneath of crown; SWC-BR: soil water content between rows; AT: air temperature (°C); RH: relative humidity (%); ST100: soil temperature at 100 cm; PRECIPT: precipitation (mm).

Table 8. The results of principal component regression.

	First year 2008–2009			Second year 2009–2010			Third year 2010–2011			All years 2008–2011		
	CO_2-UC	CO_2-BR	CO_2-AVG	CO_2-UC	CO_2-BR	CO_2-AVG	CO_2-UC	CO_2-BR	CO_2-AVG	CO_2-UC	CO_2-BR	CO_2-AVG
$R^{2\dagger}$	0.50	0.39	0.46	0.44	0.14	0.32	0.69	0.50	0.72	0.44	0.21	0.38
RMSEP[‡]	109	92	92	199	138	147	138	113	94	198	147	157
P [α]	***	*	***	***	ns	ns	***	***	***	***	***	***
PC1	***	ns	*	**	ns	*	***	***	***	***	**	***
PC2	ns	ns	ns	ns	ns	ns	*	*	**	ns	*	ns
PC3	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns
PC4	ns	ns	ns	ns	ns	ns	*	ns	ns	ns	ns	ns
PC5	ns	ns	ns	ns	ns	ns	ns	ns	ns	*	ns	ns
PC6	***	**	***	*	ns	*	*	ns	ns	***	ns	***
PC7	ns	**	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns
PC8	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	**	*
PC9	ns	ns	ns	ns	ns	ns	**	ns	*	***	*	***
PC10	ns	ns	ns	**	ns	ns	ns	**	**	**	*	**

[†]: Coefficient of determination; [‡]: root mean square error of estimation; [α]: model significance (P-value); *: significant at 0.05 level; **: significant at 0.01 level; ***: significant at 0.0001 level; [ns]: statistically nonsignificant; CO_2-UC: soil CO_2 emissions from crowns of trees; CO_2-BR: soil CO_2 emissions between rows; CO_2-AVG: average of CO_2-UC and CO_2-BR.

Table 9. Weights of variables in selected PCs.

	First year 2008–2009					Second year 2009–2010					Third year 2010–2011					All years 2008–2011				
Varb.[†]	PC1	PC2	PC6	PC9	PC10	PC1	PC2	PC6	PC9	PC10	PC1	PC2	PC6	PC9	PC10	PC1	PC2	PC6	PC9	PC10
SWCUC	0.08	0.02	0.18	0.01	–0.01	0.04	–0.10	–0.04	0.00	0.00	0.12	0.10	0.02	0.01	0.00	0.08	–0.04	0.05	0.01	0.00
SWCBR	0.27	–0.02	0.15	–0.01	0.01	0.35	–0.35	0.44	0.01	0.01	0.29	–0.06	0.31	–0.02	–0.01	0.31	–0.16	0.26	0.00	0.00
Airtemp	–0.35	0.13	–0.11	0.09	–0.01	–0.27	0.13	–0.25	–0.02	–0.04	–0.31	0.17	–0.26	0.09	–0.05	–0.30	0.16	–0.20	0.06	–0.03
RH	0.42	0.32	–0.04	0.01	0.00	0.58	0.12	–0.08	–0.01	0.00	0.50	0.46	–0.07	0.00	0.00	0.52	0.30	–0.06	0.00	–0.01
ST5	–0.41	0.17	–0.34	–0.04	–0.43	–0.32	0.19	–0.17	–0.20	0.18	–0.37	0.28	–0.33	–0.53	–0.24	–0.36	0.22	–0.32	–0.35	–0.28
ST10	–0.39	0.18	–0.23	–0.21	0.79	–0.29	0.18	–0.05	0.64	–0.44	–0.35	0.26	–0.11	0.31	0.77	–0.34	0.21	–0.16	0.16	0.79
ST20	–0.35	0.17	0.00	–0.17	–0.43	–0.27	0.17	0.10	–0.21	0.61	–0.31	0.23	0.08	0.60	–0.59	–0.31	0.20	0.03	0.58	–0.53
ST50	–0.29	0.17	0.41	0.82	0.09	–0.22	0.17	0.45	–0.59	–0.57	–0.28	0.19	0.41	–0.51	0.02	–0.26	0.19	0.43	–0.67	–0.09
ST100	–0.23	0.15	0.77	–0.50	–0.01	–0.17	0.15	0.70	0.40	0.27	–0.23	0.13	0.74	0.07	0.04	–0.21	0.16	0.76	0.26	0.12
Precipt.	0.22	0.86	–0.06	–0.01	0.00	0.37	0.83	0.03	0.01	0.00	0.26	0.70	0.03	0.01	0.00	0.29	0.82	–0.01	0.00	0.00

[†]: Variables: SWCUC and SWCBR: soil water contents underneath of crown and between rows, respectively; Airtemp: air temperature (˚C); RH: relative humidity (%); ST5, ST10, ST20, ST50, and ST100: respectively soil temperatures at 5, 10, 20, 50, and 100 cm depths; Precipt: precipitation (mm).

Table 10. The results of MARS modeling and important soil and environmental parameters for prediction of soil CO_2 emissions.

	Model	R^2	Root mean square error of prediction	GCV-R^2	Root mean square error of prediction (GCV)	Significant variables
First year (2008–2009)	CO_2-UC	0.6	90	0.31	114	ST100, ST50, AIRTEMP, SWC-UC
	CO_2-BR†					
	CO_2-AVG	0.64	72	0.36	91	ST10, AIRTEMP, ST50, SWC-UC, SWC-BR
Second year (2009–2010)	CO_2-UC	0.56	166	0.29	204	RH, ST100, SWC-BR
	CO_2-BR	0.35	111	0.06	131	ST20, RH, AIRTEMP
	CO_2-AVG	0.56	111	0.27	139	ST50, SWC-BR, RH
Third year (2010–2011)	CO_2-UC	0.62	141	0.54	154	ST100, SWC-UC
	CO_2-BR	0.39	112	0.34	118	ST10
	CO_2-AVG	0.76	81	0.6	103	ST100, SWC-UC, ST50, SWC-BR
All years (2008–2011)	CO_2-UC	0.58	172	0.39	201	ST100, ST50, SWC-UC, ST5, SWC-BR, RH, AIRTEMP
	CO_2-BR	0.34	133	0.15	147	ST20, AIRTEMP, ST5, ST50, PRECIPT, SWC-BR
	CO_2-AVG	0.53	136	0.34	157	AIRTEMP, ST100, ST5, RH, ST50, SWC-UC, SWC-BR

†: MARS could not produce a model for the data.

emission values were higher than the values found in this study, which can be attributed to the differences of the 2 studies in terms of crops and also climates, which had higher average temperature and precipitation rates in their study.

In similar arid environments under different crop management, earlier researchers reported high emission rates. Domenico de Dato et al. (2010) recorded annual CO_2 emissions of 34,000 to 42,000 kg ha^{-1} $year^{-1}$ under shrubland vegetation in a semiarid climate with 640 mm of precipitation. Allaire et al. (2008) recorded similarly high emission results in turfgrass at up to 20,000 kg ha^{-1} $year^{-1}$. Lessard et al. (1994) reported soil CO_2 emissions ranging from 158.9 to 1037.4 kg ha^{-1} $week^{-1}$ from soils under forest vegetation, which was 3 times higher than in adjacent cultivated sites with 18.9–494.9 kg ha^{-1} $week^{-1}$ soil CO_2 emissions. These rates were higher than our daily flux values. This is most likely due to differences in vegetation cover type and land use. Researchers reported higher soil CO_2 emissions from ecosystems such as forests and grasslands (Frank et al., 2006; Lu and Cheng, 2009; Schaufler et al., 2010; Akburak and Makineci 2013). Rayment and Jarvis (2000) reported annual CO_2 emissions of 8960 kg ha^{-1} $year^{-1}$ in forest ecosystems. In arid regions of China, Li et al. (2009) found that weekly CO_2 emissions fluctuated during the growing season, averaging 1680 kg CO_2 ha^{-1} $week^{-1}$ for grasslands in the black Chinese soils. In this system, soil respiration rate during the growing season fluctuated between 467 and 1730 kg ha^{-1} $week^{-1}$ with an average of 1018 kg ha^{-1} $week^{-1}$. For semiarid areas in Spain, the CO_2 emissions were between 285 and 1080 kg ha^{-1} $week^{-1}$ as reported by Alvaro-Fuentes et al. (2007).

Soil CO_2 emissions were always highest under the canopy relative to emission between rows. Given that root respiration can contribute up to 50% of the total soil respiration (Rastogi et al., 2002), this is an expected result. Monteith et al. (1964) reported that soil CO_2 emissions measured underneath crops had 50%–75% higher rates than fallow plots. In our system, average yearly emissions under the canopy were 52%, 63%, 56%, and 57% higher than between rows for the first, second, third, and all years, respectively. Increased emissions under the canopy result from root respiration as well as decomposition of organic matter from increased biomass inputs from both falling debris and root mass, with decay stimulated by increased soil water content from drip irrigation. Plant productivity as a driver for soil CO_2 emissions is demonstrated by the strong positive correlation (R^2 = 0.90) between litterfall and emissions in forests (Raich and Tufekcioglu, 2000), as well as the higher emissions reported under high-residue continuous corn-cropping systems relative to corn–soybean rotations with lower residue (Wilson and Kaisi, 2008).

Air temperature had the most significant positive correlation with soil CO_2 emissions, followed by soil temperature. However, significant negative correlation was observed between soil CO_2 emissions and RH and precipitation. The PCA analysis confirmed the results obtained from bivariate correlations.

Resulting R^2 values fell in a similar range to those of earlier studies. Mapanda et al. (2010) received R^2 values ranging from 0.12 to 0.48 when modeling soil CO_2 emissions using various environmental variables. In 3 years of field experiment performed in Italy, Mancinelli et al. (2010) obtained lower R^2 values ranging from 0.25 to 0.28 using soil relative water content and soil temperature to model soil CO_2 emission. Under controlled laboratory conditions, Wu et al. (2010) reported high R^2 values, ranging from 0.28 up to 0.87, using polynomial regression including soil water and temperature in the model. La Scala et al. (2003) obtained an R^2 value of 0.98 using similar environmental variables as in our study (meteorological variables and soil temperature), but they modeled only short-term temporal variability of soil CO_2 emission (3 weeks). Models by La Scala et al. (2006) had R^2 values ranging from 0.33 to 0.38 using the same parameters.

The improved performance of MARS over other methods can be explained by its capability to include nonlinear relationships as well as linear relationships. In contrast to other models, the MARS application uses all available data, since MARS is capable of dealing with highly correlated data.

In early studies, soil CO_2 emissions were modeled using linear, exponential, or nonlinear equations (cubic, quadratic) (Almaraz et al., 2009; Mapanda et al., 2010; Wu et al., 2010) separately, but MARS application incorporates both linear and nonlinear relationships by fitting local regression curves at subregions and including higher-order interactions among predictors (Friedman, 1991). MARS has been used with other materials (Srivastava and Solanky, 2003; Put et al., 2004) and was reported to give better results as compared to other linear and nonparametric regression techniques like generalized linear models, artificial neutral networks, and classification and regression trees.

The MARS technique establishes the order of parameter significance, with soil temperature repeatedly selected as the most significant parameter in our application. Soil temperature was statistically significant ($P < 0.05$) while soil water content was insignificant ($P > 0.05$), except in a few cases. This is in contrast to studies (Kosugi et al., 2007; Panosso et al., 2009) that reported that soil water content was the most effective parameter to estimate seasonal variation of soil CO_2 emissions in tropical regions where soil temperature does not fluctuate seasonally. Soil water content in our study was kept at optimum levels using drip irrigation. Similar to our results, Panosso et al. (2009) did not get a significant relationship between soil CO_2 emissions and soil temperature, since during the course of their experiment, soil temperature was always around optimum conditions for microbial activity. Our results concur with those of Panosso et al. (2009) and Danevcic et al. (2010), who suggested that as long as soil water content is optimal for microbial activity, soil temperature is positively related to soil CO_2 emissions. According to Mancinelli et al. (2010), the effect of soil water content on soil CO_2 emissions is complex, and its effect is more distinguishable when the soils are either too wet or too dry. Schaufler et al. (2010) demonstrated the highest soil CO_2 emissions at intermediate soil water content levels, as soil respiration was reduced under very dry or very wet conditions. Under arid conditions similar to those of our study site, Morell et al. (2010) found that the control of soil water content on CO_2 emissions was clearer when soil water content was in limited abundance, in which case increases in soil water content increased soil CO_2 emissions. Similarly, Rayment and Jarvis (2000) reported that soil CO_2 emissions become sensitive to soil water content when it is under a critical level. Schwendenmann et al. (2003) reported that the major factor affecting temporal variation in emissions was soil water content.

The interactions between soil and air temperature and between soil water and rainfall were significant, especially in the model run for the data set covering all 3 years (2008–2011) (Table 2). Lu and Cheng (2009) discussed soil CO_2 emissions as a result of interactions among temperature, water content, soil properties, and the decomposition of organic materials. Morell et al. (2010) also found significant interaction effects of rainfall and soil temperature.

In conclusion, CO_2 emissions were higher than those obtained from other agricultural systems. The highest soil CO_2 emissions were obtained in the third year (2010–2011), which was the hottest and driest period. Carbon dioxide emissions varied significantly depending on the time of the year and sampling location (under canopy versus between rows). Soil CO_2 emissions were higher under the canopy than in the area between the orchard rows and this difference was statistically significant ($P < 0.01$). The models applied to available environmental variables revealed that soil CO_2 emissions were mostly impacted by soil and air temperature, and the interactions between soil temperature and soil water content were significant and further explained the variations in soil CO_2 emissions. MARS generally outperformed MLR and PCR in modeling overall variation in weekly soil CO_2 emissions. All methods indicated the significance of soil temperature in explaining the temporal variation in weekly soil CO_2 emissions. Overall, the results suggest that available meteorological data can be used in estimating the soil CO_2 emissions in areas similar to the study area.

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References

Akburak S, Makineci E (2013). Temporal changes of soil respiration under different tree species. Environ Monit Assess 185: 3349–3358.

Allaire SE, Dufour-L'Arrivee C, Lafond JA, Lalancette R, Brodeur J (2008). Carbon dioxide emissions by urban turfgrass areas. Can J Soil Sci 88: 529–532.

Almaraz JJ, Mabood F, Zhou X, Madramootoo C, Rochette P, Ma B, Smith DL (2009). Carbon dioxide and nitrous oxide fluxes in corn grown under two tillage systems in southwestern Quebec. Soil Sci Soc Am J 73: 113–119.

Alvaro-Fuentes JA, Cantero-Martinez C, Lopez MV, Arrue JL (2007). Soil carbon dioxide fluxes following tillage in semiarid Mediterranean agroecosystems. Soil Till Res 96: 331–341.

Bouyoucos GJ (1926). Estimation of the colloidal material in soils. Science 64: 362.

Danevcic T, Mandic-Mulec I, Stres B, Stopar D, Hacin J (2010). Emissions of CO_2, CH_4, and N_2O from Southern European peatlands. Soil Biol Biochem 42: 1437–1446.

Domenico de Dato G, De Angelis P, Sirca C, Beier C (2010). Impact of drought and increasing temperatures on soil CO_2 emissions in a Mediterranean shrubland (*gariga*). Plant Soil 327: 153–166.

Edwards NT (1982). The use of soda-lime for measuring respiration rates in terrestrial systems. Pedobiologia 23: 321–330.

Friedman JH (1991). Multivariate adaptive regressions splines. Ann Stat 19: 1–67.

Grogan P (1998). CO_2 flux measurement using soda lime: correction for water formed during CO_2 adsorption. Ecology 79: 1467–1468.

Iqbal J, Lin S, Hu R, Feng M (2009). Temporal variability of soil-atmospheric CO_2 and CH_4 fluxes from different land uses in mid-subtropical China. Atmos Environ 43: 5865–5875.

Janssens IA, Ceulemans R (1998). Spatial variability in forest soil CO_2 efflux assessed with a calibrated soda lime technique. Ecol Lett 1: 95–98.

Janzen HH (1993). Soluble salts. In: Carter MR, editor. Soil Sampling and Methods of Analysis. Boca Raton, FL, USA: CRC Press, pp. 161–166.

Kacar B (1994). Soil and Plant Analysis III - Soil Analysis. Ankara: Ankara University Agricultural Faculty.

Keith H, Wong SC (2006). Measurement of soil CO_2 efflux using soda lime absorption: both quantitative and reliable. Soil Biol Biochem 38: 1121–1131.

Kosugi Y, Mitani T, Ltoh M, Noguchi S, Tani M, Matsuo N, Takanashi S, Ohkubo S, Nik AR (2007). Spatial and temporal variation in soil respiration in a Southeast Asian tropical rainforest. Agric For Met 147: 35–47.

Knudesen D, Peterson GA, Pratt PF (1982). Lithium, sodium, and potassium. In: Page AL, Miller RH, Keeney DR, editors. Methods of Soil Analysis, Part 2. Madison, WI, USA: ASA and SSSA, pp. 403–430.

La Scala N Jr, Bolonhezi D, Pereira GT (2006). Short-term soil CO_2 emission after conventional and reduced tillage of a no-till sugar cane area in southern Brazil. Soil Till Res 91: 244–248.

La Scala N Jr, Panosso AR, Pereira GT (2003). Modelling short–term temporal changes of bare soil CO_2 emissions in a tropical agrosystem by using meteorological data. Appl Soil Ecol 24: 113–116.

Lal R (2003). Global potential of soil C sequestration to mitigate the greenhouse effect. Crit Rev Plant Sci 22: 151–184.

Lessard R, Rochette P, Topp E, Pattey E, Desjardins RL, Beumont G (1994). Methane and carbon dioxide fluxes from poorly drained adjacent cultivated forest sites. Can J Soil Sci 74: 139–146.

Li H, Han X, Qiao Y, Hou X, Xing B (2009). Carbon dioxide emission from black soil as influenced by land-use change and long-term fertilization. Commun Soil Sci Plan 40: 1350–1368.

Lindsay WL, Norvell WA (1978). Development of a DTPA soil test for zinc, iron, manganese, and copper. Soil Sci Soc Am J 42: 421–428.

Lu X, Cheng G (2009). Climate change effects on soil carbon dynamics and greenhouse gas emissions in *Abies fabri* forest of subalpine, southwest China. Soil Biol Biochem 41: 1015–1021.

Mancinelli R, Campiglia E, Di Tizio A, Marinari S (2010). Soil carbon dioxide emission and carbon content as affected by conventional and organic cropping systems in Mediterranean environment. Appl Soil Ecol 46: 64–72.

Mapanda F, Mupini J, Wuta M, Nyamangara J, Rees RM (2010). A cross–ecosystem assessment of the effects of land cover and land use on soil emission of selected greenhouse gases and related soil properties in Zimbabwe. Eur J Soil Sci 61: 721–733.

McLean EO (1982). Soil pH and lime requirement. In: Page AL, Miller RH, Keeney DR, editors. Methods of Soil Analysis, Part 2. Madison, WI, USA: ASA and SSSA, pp. 199–223.

Monteith JL, Szeicz G, Yabuki K (1964). Crop photosynthesis and the flux of carbon dioxide below the canopy. J Appl Ecol 1: 321–327.

Morell FJ, Alvaro-Fuentes J, Lampurlanes J, Cantero-Martinez C (2010). Soil CO_2 fluxes following tillage and rainfall events in a semiarid Mediterranean agroecosystem: effects of tillage systems and nitrogen fertilization. Agr Ecosyst Environ 139: 167–173.

Olsen SR, Sommers LE (1982). Phosphorus. In: Page AL, Miller RH, Keeney DR, editors. Methods of Soil Analysis, Part 2. Madison, WI, USA: ASA and SSSA, pp. 403–430.

Panosso AR, Marques J Jr, Pereira, GT, La Scala N Jr (2009). Spatial and temporal variability of soil CO_2 emission in a sugarcane area under green and slash-and-burn managements. Soil Till Res 105: 275–282.

Peng Q, Dong Y, Qi Y, Xiao S, He Y, Ma T (2001). Effects of nitrogen fertilization on soil respiration in temperate grassland in Inner Mongolia, China. Environ Earth Sci 62: 1163–1171.

Put R, Xu QS, Massart DL, Heyden YV (2004). Multivariate regression splines (MARS) in chromatographic quantitative structure-retention relationship studies. J Chromatogr A 1055: 11–19.

Raich JW, Tufekcioglu A (2000). Vegetation and soil respiration: correlations and controls. Biochemistry US 51: 71–90.

Rastogi M, Singh S, Pathak H (2002). Emission of carbon dioxide from soil. Curr Sci India 82: 510–517.

Rayment MB, Jarvis PG (2000). Temporal and spatial variation of soil CO_2 efflux in a Canadian boreal forest. Soil Biol Biochem 32: 35–45.

Sauerbeck DR (2001). CO_2 emissions and C sequestration by agri-culture – perspectives and limitations. Nutr Cycl Agroecosys 60: 253–266.

Schaufler G, Kitzler B, Schindlbacher A, Skiba U, Sutton MA, Zechmeister-Boltenstern S (2010). Greenhouse gas emissions from European soils under different land use: effects of soil moisture and temperature. Eur J Soil Sci 61: 683–696.

Schwendenmann L, Veldkamp E, Brenes T, O'Brien JJ, Mackensen J (2003). Spatial and temporal variation in soil CO_2 efflux in an old-growth neotropical rain forest, La Selva, Costa Rica. Biochemistry US 64: 111–128.

Smith WN, Desjardins RL, Pattey E (2000). The net flux of carbon from agricultural soils in Canada 1970-2010. Global Change Biol 6: 557–568.

Srivastava MS, Solanky TK (2003). Predicting multivariate response in linear regression model. Commun Stat 32: 389–409.

Tufekcioglu A, Ozbayram AK, Kucuk M (2009). Soil respiration in apple orchards, poplar plantations and adjacent grasslands in Artvin, Turkey. J Environ Biol 30: 815–820.

Wu X, Yao Z, Bruggemann N, Shen ZY, Wolf B, Dannenmann M, Zheng X, Butterbach-Bahl K (2010). Effects of soil moisture and temperature on CO_2 and CH_4 soil-atmosphere exchange of various land use/cover types in a semi-arid grassland in Inner Mongolia China. Soil Biol Biochem 42: 773–787.

Zhang D, Sun X, Zhou G, Yan J, Wang Y, Liu S, Zhou C, Liu J, Tang X, Li J et al. (2006). Seasonal dynamics of soil CO_2 effluxes with responses to environmental factors in lower subtropical forests of China. Sci China Ser D 49: 139–149.

Wilson HM, Al-Kaisi MM (2008). Crop rotation and nitrogen fertilization effect on soil CO_2 emissions in central Iowa. Appl Soil Ecol 39: 264–270.